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Condition-based Maintenance: Model vs. Statistics A Performance Comparison

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Abstract

The current development in industrial applications shows a variety of approaches to perform maintenance: With reactive maintenance, only parts which fail will be replaced. This causes high costs and high unexpected failure rates. Preventive maintenance uses a predefined service plan and also a wear part exchange schedule. The plan or schedule is often based on real-time or an operation time. This often results in fixed maintenance cycles or an operation time-based maintenance. This can lead to a replacement or maintenance of a completely healthy component or to ignoring components that need to be replaced more frequently. Condition-based maintenance is an advanced approach which is based on measured component data to identify the current status of a component. This status is used to determine the date of maintenance or exchange as estimated end of life. Thus, only damaged components are maintained or exchanged. The scope of this paper is to implement a model-based maintenance algorithm in a real industrial application to determine the remaining lifetime of a component. A very important requirement is a good identification process for the model and the component. However, short commissioning times and a variety of different components pose an increased effort to identify the parameters. Thus, this paper presents an approach for a parameter identification which solely relies on data being present in the numerical control of the machine. The model-based approach is then compared to a simpler statistical approach using data from a running production machine.

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Keywords: Industrie 4.0, Predictive Maintenance, Model Based Maintenance, Condition Monitoring

1. Introduction

The current development in industrial applications shows a variety of different approaches to maintenance. All approaches from purely reaction driven maintenance to condition-based maintenance represent an important cost and time factor during machine operation.

Today, maintenance is conducted in planned intervals to maximize uptime and production efficiency. However, these intervals only take into account a very conservative lifetime estimate, based on worst case experiences, although the exact load case, mounting configuration, the load on the bearings, improper use, and further lifetime enhancing or shortening conditions are not considered. Another problem is improper usage of components which can lead to a very short lifetime. Thus, poor communication of user errors (such as crashes, bad handling, etc.) can lead to unexpected downtimes which can severely hinder the production. To overcome the issue of complete ignorance of the current machine condition, a live monitoring to support condition-based maintenance is key for future production lines to reduce machine downtimes, which can span up to several days when an unwanted error occurs in a difficult component.

A first approach to condition-based maintenance for an electrical spindle is introduced in this paper, using a real-world example. The scope of this work is to implement a model-based algorithm in a real industrial application to determine the remaining lifetime of a component. Thus, it is crucial to have a good identification process for the model and the component. Identifying the models parameters of different components using external measurement devices pose an increased workload and thus would not be feasible. The goal of this work is to present an approach to parameter identification which solely relies on status data, present on the numerical control of the machine. State-of-the-art motor controllers contain a set of data (current, voltage, position) which allow a parameter identification to be conducted online, without any further effort. The resulting lifetime extrapolation can be conducted using an extrapolation of the identified parameters.

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2. Motivation

There are many approaches to condition monitoring of spindle drives and synchronous machines, such as the frequency response methods presented by [1] and [2], or various parameter identification methods as presented by [3].

However, these methods rely on a large set of data, usually measured under laboratory conditions. Since a standard industry application should be used in this paper, the goal is to get the necessary information without additional sensors, but to use data form the machine control instead. This allows identifying the component when it is already built into the machine. Without a complicated test procedure the parameter identification will be run during commissioning and with some experience from former application cases.

A first approach in this work is an overall identification of the full system using a third-order model with seven unknown parameters. Batch algorithms, such as least squares and prediction error methods as presented in [4] were used in a first step. Using standard process trajectories, these processes yielded bad conditioning and poor performance. To overcome these problems, an adequate excitation had to be considered. However, the complexity of the model made it hard to define an useful trajectory for the identification process.

To reduce the number of parameters for the identification step, the system was divided into several subsystems. For each subsystem a specific excitation signal is used. The excitation signal is based on a physical analysis of the differential equations (1) and (2). With these excitation signals, a simplification of the model and the identification algorithm was achieved, which will be described in this paper.

A second approach is a purely statistical algorithm based on the measured data. This purely mathematical approach does not allow further insight into the resulting data, can however be run in parallel to the normal machine operation and does not require special excitation signals.

The condition estimation, which will be described in the end can be applied to both approaches and is the basis of a condition-based maintenance. The two approaches each offer unique benefits which will be presented in the concluding words.

3. Model of a Spindle Drive

In literature, there are several approaches to model a synchronous drive, which range from detailed models of magnetic flux as presented by [5] to simple models as presented by [6]. The model used in this work is based on the simple model with some further additions.

3.1. Electrical Model

The electrical model, as presented by [6] is shown in (1) and (2).

$$L_s \frac{\mathrm{d}I_d(t)}{\mathrm{dt}} = U_{sd} - RI_d + pL_s\omega_m I_q \tag{1}$$

$$L_s \frac{\mathrm{d}I_q(t)}{\mathrm{dt}} = U_{sq} - RI_q - pL_s\omega_m I_d - \tfrac{3}{2}p\omega_m\Psi_0 \tag{2}$$

The electrical parameters consist of L_s the inductance of the windings, R the resistance of the windings, Ψ_0 the motor constant and p the number of pole pairs. U_{sd} and U_{sq} represent the control action voltages, I_q describes the acting current in the motor and I_d the blind current respectively. ω_m represents the angular velocity of the motor shaft. The current I_q is directly responsible for the torque acting on the motor shaft, whereas I_d has no effect and describes the loss in the motor. Therefore I_d will be controlled to be 0 by the current controller of the motor.

The model of the three-phase electrical system is based on a coordinate transformation from a three-phase AC voltage to a two-dimensional DC voltage representation. This DC representation in d,q - coordinates is based in the rotor coordinate system, eliminating all AC effects. The coordinate transformation is depicted in Figure 1.

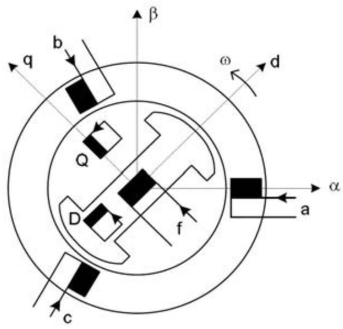

Fig. 1. 3-phase Model by [7]

3.2. Mechanical Model

The model of the connected spindle mechanics looks as follows:

$$\Theta_{tot}\frac{\mathrm{d}\omega_m(t)}{\mathrm{dt}} = \tfrac{3}{2}p\Psi_0 I_q - \mu_s \mathrm{sign}(\omega_m(t)) - \mu_v\omega_m(t) - F_p\frac{n10^{-3}}{2\pi\gamma} \tag{3}$$

which describes a mechanical architecture as depicted in Figure 2.

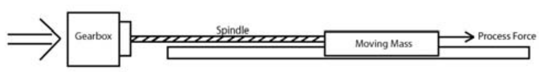

Fig. 2. Mechanical Architecture

The mechanics consist of a gearbox with transmission ratio γ and a spindle with an increment of n mm per revolution. The moving mass, the inertia of the spindle, gearbox and motor are all lumped into one parameter Θ_{tot} which describes the total inertia of the system. The process force, which acts on the linear moving mass is described as F_p. Additionally, a speed dependant friction model is used, with coefficients μ_s and μ_v which consist of the friction of the moving mass on the bearings, the friction of the spindle nut and the gearbox friction. The friction is speed-dependant with a static friction part μ_s and a dynamic friction part μ_v.

4. Parameter Identification

In this section, the parameter identification process will be described. Each parameter will be analyzed in detail and identified.

4.1. Test equipment

The system consists of a synchronous motor[1] which is directly mounted on a spindle with a 10 mm increment per revolution as shown in Figure 3. This means that the setup has the following parameters:

$$\gamma = 1 \qquad n = 10 \qquad p = 5 \tag{4}$$

Fig. 3. Motor setup in the testing environment

The trajectory is depicted in Figure 4.

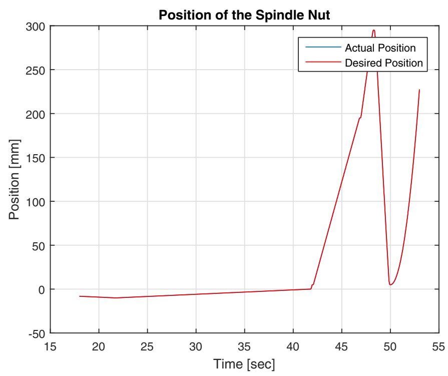

Fig. 4. Trajectory of the test setup

The starting point of the trajectory in point 1 is on a fully compressed spring. The trajectory to point 2 releases the spring with a velocity of 0.5 mm/s in a distinct force-position curve[2]. In point 2 the spring is fully released. The trajectory 2-3 is defined by a constant velocity of 40 mm/s and from 3-4 by a constant velocity of 80 mm/s. From 4-5 the spindle is positioned back to the starting position 5. In part 5-6 a constant acceleration of 20 mm/s^2 is conducted.

4.2. Trajectory 1-2

Part 1-2 of the trajectory depicted in Figure 4 is run with a slow and constant speed (0.5 mm/s) at a high load F_p (> 20% of maximum motor torque) imposed by the spring. It is assumed that the friction terms $\mu_s \text{sign}(\omega_m) + \mu_v \omega_m$ are unknown a-priori. However, for a good mechanical construction it is considered to require less than 1 % of the maximum torque of the motor[3]. Because of a constant speed, the term $\frac{\mathrm{d}\omega_m(t)}{\mathrm{d}t}$ in (3) equals zero.

Using the above-mentioned assumptions the friction can be considered negligible compared to the process force. This leaves a simple steady-state mechanical equation (5).

$$\underbrace{\Theta_{tot}\frac{\mathrm{d}\omega_m(t)}{\mathrm{d}t}}_{0} = \frac{3}{2}p\Psi_0 I_q - \underbrace{\mu_s \text{sign}(\omega_m(t)) - \mu_v\omega_m(t)}_{0} - F_p\frac{n10^{-3}}{2\pi\gamma} \tag{5}$$

The resulting equation (5) only has one unknown parameter Ψ_0 allowing for an analytical calculation of Ψ_0

$$\Psi(t) = F_p(t)\frac{n10^{-3}}{2\pi\gamma}\frac{2}{3pI_q(t)}, \Psi_0 = \overline{\Psi(t)} \tag{6}$$

To account for the fluctuation which occurs in $\Psi(t)$, the value is averaged using a least squares method.

The force reaches 27% of maximum motor torque close to point 1 which is sufficient for the assumptions made. Using equation (6) the motor constant Ψ_0 is calculated. The data used is shown in Figure 5. The timespan for the identification is chosen close to point 1 to have a maximum possible load on the motor, thus diminishing the influence of the friction. The linear dependency between acting torque and current in the motor can be clearly seen. The least squares estimation results in (7).

$$\Psi_0 = 0.0915 \tag{7}$$

The trajectory of the measured data can be seen in Figure 5.

4.3. Trajectory 2-4

The second part of the trajectory is used to identify the friction of the system. It consists of two sub-parts with a constant velocity 40 mm/s and 80 mm/s respectively, yielding $\frac{\mathrm{d}\omega_m(t)}{\mathrm{d}t} = 0$ in (3). There is no external load applied to the system. Using such a trajectory yields a steady-state mechanical equation (8).

$$\underbrace{\Theta_{tot}\frac{\mathrm{d}\omega_m(t)}{\mathrm{d}t}}_{0} = \frac{3}{2}p\Psi_0 I_q - \mu_s \text{sign}(\omega_m(t)) - \mu_v\omega_m(t) - F_p\frac{n10^{-3}}{2\pi\gamma} \tag{8}$$

[1]Beckhoff AM 3042 synchronous motor with a Beckhoff AX5206 frequency converter

[2]Measured beforehand with a Kistler™ force sensor and a Schneeberger™ position measuring system

[3]This assumption is very important and holds for all observed installations

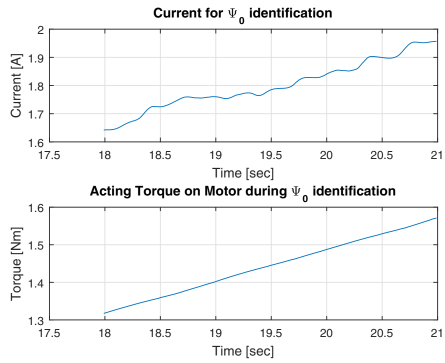

Fig. 5. Ψ_0 identification, low force included

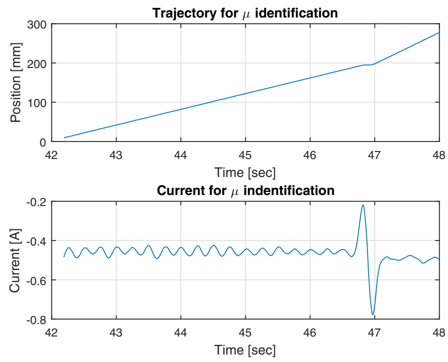

Fig. 7. μ extrapolation trajectories

With no external load applied to the system, F_p is equal to the gravitational force mg, which is very small compared to the spring force. It is no longer possible to neglect the friction in the system. However, as the motor constant Ψ_0 is already identified, there is now the possibility to identifiy the friction term (9).

$$\mu(\omega_m) = \mu_s \mathrm{sign}(\omega_m) + \mu_v \omega_m \tag{9}$$

Replacing (9) in (8) the friction will be identified as in (10).

$$\mu(\omega_m) = \tfrac{3}{2} p \Psi_0 I_q - F_p \tfrac{n 10^{-3}}{2\pi\gamma} \tag{10}$$

The linear dependency on the velocity will be identified using a linear extrapolation as depicted in Figure 6.

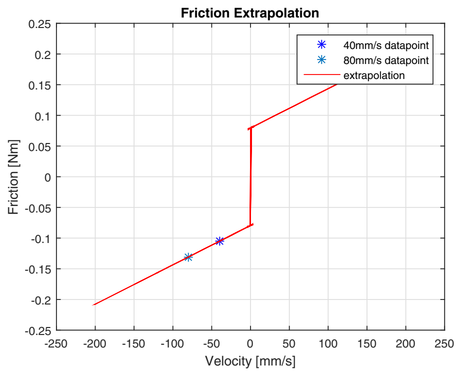

Fig. 6. μ extrapolation

The identified values for two speeds are shown in Figure 6 and are reduced to a mean value (11) using least squares.

$$\mu_s = 0.0795 \qquad \mu_v = 6.4121 \cdot 10^{-4} \tag{11}$$

The trajectories used to identify these values are depicted in Figure 7. The spindle is run at 40 mm/s and 80 mm/s respectively. The ripples in the plot are due to the spindle increment, which imposes some vibration to the motor.

4.4. Trajectory 5-6

The third part of the trajectory consists of a part with constant acceleration. The identification of the inertia Θ_{tot} relies on (3) and thus needs to have a dynamic component to guarantee, that $\frac{\mathrm{d}\omega_m(t)}{\mathrm{dt}} \neq 0$. This means, that the inertia will be identified using

$$\Theta_{tot} \frac{\mathrm{d}\omega_m(t)}{\mathrm{dt}} = \tfrac{3}{2} p \Psi_0 I_q - \mu_s \mathrm{sign}(\omega_m(t)) - \mu_v \omega_m(t) - F_p \tfrac{n 10^{-3}}{2\pi\gamma} \tag{12}$$

The force $F_p(t)$ is equal to the gravitational force in this case, as no external load is applied to the motor.

To identify Θ_{tot} a batch least squares approach is used as shown in (13).

$$\underbrace{\begin{bmatrix} \frac{3}{2} p \Psi_0 I_1 - \mu_s \mathrm{sign}(\omega_1) - \mu_v \omega_1 - F_{p,1} \frac{n 10^{-3}}{2\pi\gamma} \\ \frac{3}{2} p \Psi_0 I_2 - \mu_s \mathrm{sign}(\omega_2) - \mu_v \omega_{m,2} - F_{p,2} \frac{n 10^{-3}}{2\pi\gamma} \\ \vdots \\ \frac{3}{2} p \Psi_0 I_n - \mu_s \mathrm{sign}(\omega_n) - \mu_v \omega_n - F_{p,n} \frac{n 10^{-3}}{2\pi\gamma} \end{bmatrix}}_{b} = \underbrace{\begin{bmatrix} \frac{\mathrm{d}\omega_1}{\mathrm{dt}} \\ \frac{\mathrm{d}\omega_2}{\mathrm{dt}} \\ \vdots \\ \frac{\mathrm{d}\omega_n}{\mathrm{dt}} \end{bmatrix}}_{A} \Theta_{tot} \tag{13}$$

The parameter is then given by (14)

$$\Theta_{tot} = (A^{\mathrm{T}} A)^{-1} (A^{\mathrm{T}} b) \tag{14}$$

Which, in this case, yields (15).

$$\Theta_{tot} = 0.000468 \tag{15}$$

4.5. Verification

To cross-validate this method, a different trajectory was run on the same test equipment and compared to the modeled data. A set of three different speeds was run (200mm/s, 120mm/s and 40mm/s), which resemble a realistic operation in a state-of-the-art assembly line. The verification results are depicted in Figures 8 and 9.

It is important to emphasize the incentive of this work, to only use data which can be obtained from the controller of the electric motor. With this data only, it is possible to identify the

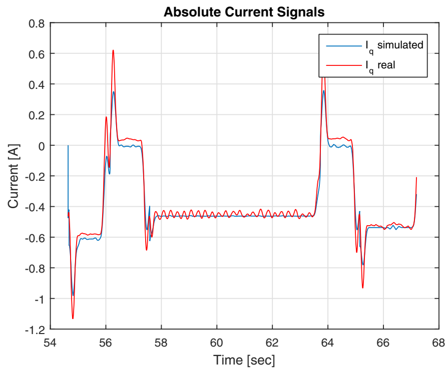

Fig. 8. Current verification trajectories

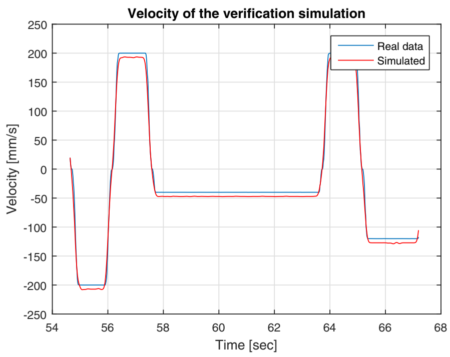

Fig. 9. Speed verification trajectories

parameters of the built in and running system, which takes into account all the mechanics present in the machine and avoiding a complicated test setup.

5. Statistical Model

In contrast to the parameter identification method presented above, this section concentrates on a statistical approach to condition monitoring. This approach solely relies on data available from the motor controller, therefore no analytical model is required. Since no parameters are identified, no direct statement about the motor constant, the total inertia or the friction is made. Rather, specific signal features are observed and compared to the nominal case. To obtain a statement about the condition of the drive, these signal features have to be chosen accordingly.

5.1. Control Charts

Control charts originate from statistical process control, [8]. In this work, they are used as a tool to analyze accruing process data. A prerequisite to use control charts is, however, that process signals from the drive in the nominal, fault free case are available. This data set is usually acquired during commissioning.

During operation, the drive is monitored and its signals are compared to the nominal case automatically. Hence, condition monitoring with control charts involves two phases: teaching and analysis.

5.2. Teaching

To use control charts, the continuous signals (or large sample size discretized signals) available from the motor controller are reduced to meaningful single points. First, an appropriate signal has to be chosen. As shown in Section 4, the current signal contains information about load, friction and the motor itself and is therefore appropriate for condition monitoring. In a second step, one or more suitable features from the current signal out of one working cycle are selected, see Figure 8. To define a feature, a time interval is selected. Then, an attribute is assigned, e.g. minimum, maximum or mean value of the signal in the selected interval.

The selection of the signal, time interval and attribute defines which characteristic of the drive is monitored; this is comparable to the identification of the parameters in Section 4. For example, if the friction of the system should be monitored, the current signal in trajectory 2-3 or 3-4, see Figure 7, is selected. The mean current value in the interval $t = [43, 46]$ represents the viscous friction μ_v and the current peaks in the interval $t = [46, 48]$ represent the static friction μ_s, given a constant total inertia Θ_{tot}.

After reducing continuous time signals to single observations, the data of N cycles is used to calculate the control limits CL of the control chart, where usually $N > 25$. When using the exponentially weighted moving average EWMA control chart, which is suitable when small shifts have to be detected, the steady state upper and lower control limits, UCL and LCL, are given by:

$$UCL = \mu_0 + \frac{L\sigma}{\sqrt{N}} \sqrt{\frac{\lambda}{(2-\lambda)}} \tag{16}$$

$$LCL = \mu_0 - \frac{L\sigma}{\sqrt{N}} \sqrt{\frac{\lambda}{(2-\lambda)}} \tag{17}$$

where μ_0 is the target value, σ is the process variation and L and λ are design parameters. Common choices for the smoothing factor are $0.05 <= \lambda <= 0.25$ and $L = 3$ for the sigma multiplier, which corresponds to the usual three-sigma limits. Since target value and process variation are unknown, they are estimated from the data set:

$$\mu_0 = \hat{\mu} \quad \text{and} \quad \sigma = \hat{\sigma} \tag{18}$$

The exponentially weighted moving average is defined as:

$$y_i = \lambda x_i + (1-\lambda) y_{i-1} \tag{19}$$

where x are the observations and i is the sample number. After calculating the control limits and the statistic y_i, the EWMA chart is plotted. If all points y_i lie inside the control limits, the process is said to be under statistical control. Otherwise, outliers are investigated, looking for assignable causes. After working on these causes to improve the process, outliers are excluded and the control limits are recalculated.

5.3. Analysis

During operation, the drive is monitored automatically by extracting single points of interest from controller signals, calculating the EWMA statistic and applying the control limits. If the EWMA statistic exceeds the control limits, the process is out of control, implying that the drive is in a condition different then the taught nominal case. In such a degraded state, a failure of the component is likely, and maintenance actions have to be taken.

5.4. Benefits

The following advantages arise from the statistical approach:

- Minimal user input is required, condition monitoring is possible without modelling.
- Automated teaching is possible for different drives with a similar working cycle.
- In reasonable cases, a reteaching of the control limits is possible.

6. Condition Estimation

Using the model of the electrical axis, an online parameter estimation can be done to analyze the state of the axis. Critical parameters such as friction, torque and controller quality can be observed to give a clear view on the condition of the component. Using the procedure described above one can conduct a parameter estimation without further test equipment or a special test stand. This allows for an online, e.g. built into a machine, application of the algorithm mentioned above. The performance is promising, as shown in chapter 4.5. In the following section the two approaches as presented in Section 4, which focuses on the model based parameter identification approach, and Section 5, which focuses on a statistical process control approach, are compared.

6.1. Requirements

To conduct a parameter identification the spring has to be inserted into the axis and the trajectory has to be conducted. This needs 30 seconds, in which the machine can not produce. For a machine in production, this can lead to critical downtimes. Here, the statistical approach can be run in parallel to the production. This has several positive impacts:

Timing: The time needed for the statistical condition estimation is zero. While the algorithm can run in parallel the parameter estimation has to be conducted, while the machine is not producing.

Significance of data: The statistical approach uses directly the data from the process itself. It allows for several different condition estimations, such as process- and cycle time monitoring.

Ease of use: The statistical monitoring uses data from the process itself, which is easily understood by process engineers working with the machine. The abstract data from the parameter estimation requires no connection to the process itself

Condition monitoring: The condition monitoring using the parameter identification is more detailed than the statistical approach. It allows a direct conclusion on which component is damaged and which parameter is out of range. The statistical approach just delivers data **if** the whole component is damaged or not

7. Conclusion and Outlook

To conclude this work the two approaches, model-based and purely statistical, offer each unique benefits. Whereas the statistical approach can be run in parallel to the production process and is currently favored by process engineers, the model-based approach offers a detailed view into the actual condition of the spindle drive.

The parameter estimation can locate a possible problem much more precisely without the need of an extensive teaching. The problem however is the trajectory which has to be run during machine operation from time to time. The whole process for a skilled operator takes approximately 30 seconds to conduct. A decrease in possible production output is still the worst case scenario, compared to an unwanted halt of a machine. The statistical approach on the other hand offers an online calculation of the condition based on process control theory. It can be run in parallel with the operation of the machine and offers an automated teaching, if applicable. The outcome of the statistical algorithm is, however, not as precise as the model based algorithm. It can not differentiate between a rise in process force, change of production material or component wear in the first place. Although, all these problems need to be analyzed, it is not possible to prioritize certain errors, without further analysis of educated personal.

A test in an industrial machine is planned for Spring 2016, where the whole algorithm (both model-based and statistical) will be implemented on a large scale automated machine to verify the presented approaches and results. Using an industrial implementation the lifetime condition extrapolation can be tested and validated, which is the next step in this work.

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